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COMPLEXITY, UNCERTAINTY, AND SYSTEMATIC ERROR IN HYDROLOGIC MODELS

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Abstract Issues of complexity, parameter and input variable uncertainty, and systematic model errors are reviewed and assessed. Simple measures are derived to represent degree of complexity, degree of uncertainty, and degree of systematic error for a simple subset of hydrologic models. Model complexity is represented by a complexity number, Nc = nm + 1. The quantity n is the number of model parameters and input variables and m is the number of simulation runs (around base or nominal values) required to assess noninteractive model sensitivity. Model uncertainty is represented by a summed coefficient of variation, CVm, computed from the sum of the individual coefficients of variations of the n parameters and input variables. Systematic error, NSm, is related to how well the model mimics nature and is represented as a function of the number of the basic concepts of conservation of mass, momentum, and energy, and of the basic variables position, velocity, and acceleration included in each model component. Three infiltration models: Phi Index, Runoff Curve Number, and the Green-Ampt Infiltration Equation; Two peak discharge estimation procedures: The Rational Formula and the coupled Green-Ampt Kinematic Wave Model are used as example illustrations. These examples are used to illustrate the highly interactive and important concepts of model complexity, uncertainty, and systematic error. The model quantification methodology and examples are also used to formulate the hypothesis that simple measures can be derived and used to objectively evaluate model complexity and its relationships with uncertainty and systematic error. Possible future applications of the model quantification methodology include selection of appropriate simulation models within decision support systems and contributions to development of a systematic approach for development and application of appropriate technology.

1. Introduction

Hydrologic modeling is a scientific activity which requires abstraction and simplification of processes occurring in nature. This abstraction and simplification constitutes an essential part of modern scientific procedure (i.e. see Rosenblueth and Wiener, 1945). Compared with the entirety of earth science and engineering, hydrologic modeling is a small and new science. Almost all quantitative work in model conceptualization has been accomplished during this century, with most progress made since the advent of the digital computer as a research and development tool.

V. P. Singh and B. Kumar (eds.), Surface-Water Hydrology, 175–189.

Because it is new and in a period of rapid transition, hydrologic modeling is diverse in its concepts and applications. The general topic of hydrologic modeling on small watersheds was recently and comprehensively summarized by Haan, *et al.* (1982). Goodrich and Woolhiser (1991) reviewed the U.S. literature from 1986 to 1990 and concentrated on entire watershed, or catchment, response rather than on components or processes. They concluded "...a detailed, process based, understanding of hydrologic response over a range of catchment scales (0.01-500 km^2) still eludes the hydrologic community." This assessment is in agreement with an earlier one by Dunne (1982) but is not as optimistic for the future as the views of Rogers and Anderson (1987) or Bevin (1987). Anderson and Burt (1985) edited a volume of papers on forecasting in hydrology including a brief, but broad-based, introduction to modeling strategy (Anderson and Burt, 1985, Ch. 1 Modeling Strategies).

Hydrologically driven water quality modeling was recently summarized in the proceedings of a 1988 conference (DeCoursey, 1990). Beck (1987) presented a comprehensive review of analysis of uncertainty in water quality modeling and questioned whether more complex models were better given their increased uncertainty. Hydrologically driven soil erosion modeling within the U.S. Department of Agriculture was recently summarized by Lane, *et al.* (1993). These reviews, while not restricted to hydrologic modeling, illustrated the key role hydrologic modeling plays in natural resource models.

These summary or synthesis books and papers held a common theme as they reviewed historical and recent developments in the general areas of hydrologic modeling and modeling based on hydrologic models (water quality and soil erosion). This common theme included the general assessment that models are increasing in complexity with time. Discussion of model complexity, uncertainty, and errors are explicit throughout these and other reviews. Unfortunately, these difficult issues are usually dealt with qualitatively and heuristically. Often the most useful insights are presented in almost anecdotal form (i.e. Todini, 1988; Wagenet, 1988; and Bevin and Jakeman, 1990).

Our central thesis here is that if further progress is to be made in understanding model complexity, uncertainty, and errors, then quantitative measures must be developed to express these concepts analytically or statistically. Further, it is our belief that this quantitative approach must involve simple measures if they are to be useful at this stage in hydrologic modeling. We seek insight through simplicity and do not intend to introduce additional complexity in an already complex and easily misunderstood area of hydrologic modeling.

1.1 CLASSIFICATION OF MATHEMATICAL MODELS

Classification of hydrologic models was summarized by Woolhiser and Brakensiek (1982) and included the broad classifications of material models and formal or mathematical models. It is the second category that is of interest herein. They listed six criteria to use in classifying mathematical hydrologic models as: (1) Model subject and structure, (2) Role of time, (3) Cognitive value, (4) Character of results, (5) Approach and methods of solution, and (6) Properties of the operator functions contained in the model.

Model subject and structure refer to which components of the hydrologic cycle are addressed and how the components or processes addressed are being modeled. The role of time refers to whether the processes are dynamic, that is, with time explicitly included in the formulation or static where time plays no role. The cognitive value of a model refers to whether it is conceptual, physically based, or a trend model. The character of results refers to the model's output and is generally described as stochastic (components random in time or space) or deterministic. Approach and methods of solution refer to model type (i.e. physically based) and how solutions to the model are obtained. Properties of the operator functions refers to whether the model is linear or nonlinear, lumped or distributed, or stationary or nonstationary.

Todini classified rainfall-runoff models and used the following general scheme (Todini, 1988, p. 346)

"A mathematical model in broad sense, is a combination of two basic components. The first one expresses all the *a priori* knowledge that one has on the phenomenon to be represented and can be referred to as the physical component. The second, the stochastic component, expresses in statistical terms what cannot be explained by the degree of *a priori* knowledge already introduced..."

From the physical and stochastic components, Todini assumed four classes of models based on increasing levels of the *a priori* knowledge they include: (1) Purely stochastic, (2) Lumped integral, (3) Distributed integral, and (4) Distributed differential models. Lumped and distributed have their traditional meaning and integral refers to processes represented by ordinary differential equations and differential refers to processes represented by partial differential equations.

1.2 USE OF CLASSIFICATIONS

Model classification schemes are useful in describing the general features of a model as to which components of the hydrologic cycle it simulates, how the simulation is accomplished, the type and level of mathematics involved, the nature of the model output, and the general type and amount of input information required. This knowledge is valuable in many ways. These include, but are not limited to, comparing alternative models, selecting the appropriate model for a given application, selecting data bases and experimental efforts to parameterize the model, and designing model validation analyses.

As valuable as the model classification methods are, they do have their limitations. With such schemes it is possible to classify a given hydrologic model if sufficient detail is presented in the model documentation. Given the classification results, one has a generalized picture of the model's complexity, its uncertainty, and its systematic error. However, the classification gives a generalized picture only and does not provide the analytical tools to move much beyond insight given by the anecdotal examples described earlier.

1.3 SCOPE AND PURPOSE

Hydrologic modeling discussed in this paper is limited to mathematical modeling and primary emphasis is on rainfall-runoff modeling. No attempt is made to conduct and report a state-of-the art summary or comprehensive literature search.

This paper provides a synopsis of selected examples and experiences in hydrologic modeling related to our central thesis that simple, quantitative measures must be developed to express model complexity, uncertainty, and systematic error beyond the limits of model classification techniques and to provide insight beyond those insights available through qualitative assessments. We seek to formulate and test the hypothesis that simple measures can be developed and used to objectively evaluate model complexity and its relationships with uncertainty and systematic error.

2. A Measure of Model Complexity

Measures of model complexity are implicit in the classification schemes discussed earlier. A complex model connotes one which is sophisticated and powerful but also difficult to understand, operate, and interpret. One method of investigating model complexity is through the application of sensitivity analyses.

2.1 NONINTERACTIVE SENSITIVITY ANALYSIS

Sensitivity analysis is a method of assessing the relative importance or sensitivity of a model's response or output to its parameter values or inputs. The simplest and most easily understood method of sensitivity analysis is the noninteractive method.

Given a set of model parameter values and typical values of the input variables which are in a sense representative or nominal (called the base values hereafter), computations are performed. With all other parameters and input variables fixed at their base values, individual parameters and input variables are varied about their base value, independently and sequentially, over a range of feasible and realistic values and the computations are repeated. The resulting set of output values shows how the model functions and how important changes in each parameter or input are in determining changes in the resulting output.

Weaknesses in the noninteractive sensitivity analysis procedure include: (1) Parameters and inputs are varied individually so that interactions are not determined, (2) Sensitivity of the model to changes in inputs and parameters is dependent on the choice of base values, and (3) The procedure is essentially empirical and does not draw on what is known of the model structure. Strengths of the procedure include: (1) It is straightforward and easy to perform and understand, (2) The results are amenable to tabular and graphical presentation as they are numerical and do not involve complex formulae, and (3) The procedure is independent of the model structure and is thus broadly applicable.

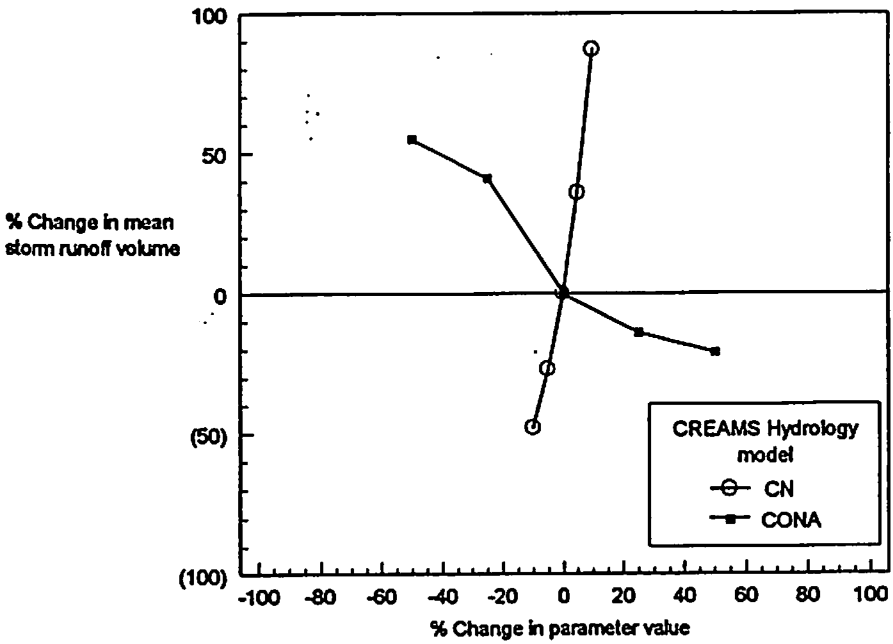
A noninteractive sensitivity analysis for the hydrologic component of the CREAMS Model (Knisel, 1980) for a small agricultural watershed at Tifton, Georgia was conducted by Lane and Ferreira (1980). Sensitivity of computed mean storm runoff volume to two parameters (CONA, a bare-soil evaporation rate parameter and CN, the Runoff Curve Number) is illustrated in Fig. 1. Changes in the parameter values and the resulting changes in mean storm runoff volume are shown as percentage changes from their base values. For example, in Fig. 1, a 50% decrease in CONA results in a 55% increase in mean storm runoff volume while a 10% decrease in CN results in a 48% decrease in storm runoff volume. The example results shown in Fig. 1 suggest that decreases in the evaporation rate parameter, CONA, result in magnified (larger changes in output than the corresponding change in the parameter value) increases in runoff while increases in CONA result in reduced (smaller changes in output than in the parameter) decreases in runoff. On the contrary, all changes in CN result in magnified changes in runoff. Thus all errors or uncertainty in CN are magnified as resulting errors in runoff while errors in CONA can result in magnified or educed errors in runoff. Finally, changes in runoff are positively correlated with changes in CN while changes in runoff are negatively correlated with changes in CONA.

2.2 MODEL COMPLEXITY NUMBER

The results of nine simulation runs are shown in Fig. 1, one run for the base values and four runs for CONA and four for CN. The general formula for the number of runs required in a noninteractive sensitivity analysis is $Nc = nm + 1$ where n is the number of parameters and input values (2 in Fig. 1) and m is the number of simulation runs around the base values required to define the sensitivity curve (4 in Fig. 1).

We propose Nc as a simple model complexity number reflecting the size of the model (as represented by the number of parameters) and the amount of input required (as represented by the number of input variables). Further, Nc reflects the complexity of the model structure and function through the number of simulation runs required to define the sensitivity curves illustrated in Fig. 1.

Figure 1. Illustration of noninteractive model sensitivity. Changes in runoff volume with changes in parameter values.



3. A Measure of Model Uncertainty

Model uncertainty can be expressed as uncertainty due to errors related to parameter and input uncertainty and those due to errors in model structure and function. The emphasis here is on uncertainty related to the parameters and inputs.

Uncertainty inherent in the model parameters and input variables result in uncertainty in model outputs (i.e. as illustrated in sensitivity analyses). Parameter and input values cannot be determined absolutely due to measurement errors in directly measurable quantities. Inferred quantities contain the uncertainty from measurement errors in the predictor variables as well as errors in the predictive relationship between the measured quantity and the inferred parameter or input. Often, one-time estimates are used to represent dynamic values and point values of parameters and inputs are used to represent spatial averages. These estimates also introduce uncertainty into the parameters and inputs and the resulting model outputs.

Uncertainty in model outputs also result from errors in model formulation (i.e. mistakes or omissions), errors in model structure (i.e. abstractions and simplifications), and errors in model implementation (i.e. coding errors, calculation errors, roundoff errors, etc.).

3.1 NONINTERACTIVE PARAMETER AND INPUT UNCERTAINTY

The coefficient of variation of a random variable is defined as the standard deviation divided by the mean. It is often used as a relative measure of uncertainty as it is dimensionless and directly related to the mean value. Thus the coefficient of variation, CV, can be used to compare relative variability between random variables of different units and scales.

Notice that the coefficient of variation for an individual parameter or input value can be used to help determine the range of variation for sensitivity analysis as illustrated in Fig. 1. Rather than using a fixed percentage change in the base value of the parameter or input (as in Fig. 1), one could use a fixed percentage of the standard deviation through the coefficient of variation.

For example, if the coefficient of variation of a parameter is 10% and the mean is taken as the base value then plus and minus 20% would be equivalent to plus and minus two standard deviations. Conversely, if the coefficient of variation of a second parameter is 20% then one would need plus and minus 40% to have a comparable plus and minus two standard deviations about the mean.

If CVp is the (1,Np) array of coefficients of variation of a model's parameters and CVi is the (1,Ni) array of coefficients of variation of a model's input variables, then an overall, noninteractive coefficient of variation for a model can be defined as

$$CVm = \sum_{p=1}^{Np} (CVp) + \sum_{i=1}^{Ni} (CVi) \qquad (1)$$

The overall coefficient of variation is a positive number and is formed from Nm = Np + Ni individual values. It is noninteractive because it does not consider covariances of the parameters or input values.

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For example, if the coefficient of variation of a parameter is 10% and the mean is taken as the base value then plus and minus 20% would be equivalent to plus and minus two standard deviations. Conversely, if the coefficient of variation of a second parameter is 20% then one would need plus and minus 40% to have a comparable plus and minus two standard deviations about the mean.

If CVp is the (1,Np) array of coefficients of variation of a model's parameters and CVi is the (1,Ni) array of coefficients of variation of a model's input variables, then an overall, noninteractive coefficient of variation for a model can be defined as

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The overall coefficient of variation is a positive number and is formed from Nm = Np + Ni individual values. It is noninteractive because it does not consider covariances of the parameters or input values.

Weaknesses of the noninteractive coefficient of variation, CVm, include: (1) It deals only with model parameters and input values, (2) It considers individual coefficients of variation and does not include interactions, and (3) It does not order, or rank, parameters in terms of their importance as determined by a sensitivity analysis. Strengths of CVm include: (1) It is straightforward and easy to calculate and understand, (2) It represents a single number and thus facilitates comparison between models, and (3) It is independent of model structure and thus broadly applicable.

Coefficients of variation for some representative values of commonly used rainfall-runoff model input variables and parameters are summarized in Table 1. Coefficients of variation from this table will be used in example calculations in a later section of this paper.

Table 1. Coefficients of variation for representative values of commonly used rainfall-runoff model input variables and parameters

Variable or Parameter	Coefficient of Variation	Source and Comments
Simulated Rainfall:		
Depth	0.04 - 0.13	3x11 m plots, ARS Rainfall Simulator Database for AZ and NV, Simanton, et al. (1986)
Int.	0.02 - 0.07	
Final Infiltration Rate*	0.26 - 0.64	
Natural Precipitation:		
Depth	0.44	12.4 sq km Goodwater Creek Watershed, a cultivated agricultural (row crops) area in Missouri, 35 largest floods in 14 years, Hjelmfelt and Kramer (1988)
Obs. Runoff**		
Vol.	0.67	
Peak	0.64	
Unit Hydrograph***		
Peak	0.19	
Time of Conc.	0.4	
Time to Peak	0.32	
Surface-Soil:		
Manning n:		
Bare-Fallow	0.7 - 0.8	Overland flow from erosion plot studies, Engman (1986) and Weltz, et al. (1992)
No Till	0.3 - 1.0	
Disk Harrow	0.3 - 1.1	
Plow	0.2 - 0.6	
Grass	0.1 - 0.2	
Rangeland	0.5 - 0.7	

Table 1 continued. Coefficients of variation for representative values of commonly used rainfall-runoff model input variables and parameters

Variable or Parameter	Coefficient of Variation	Source and Comments
Surface-Soil continued:		
Curve Number	0.08	4.5 sq km watershed W-5 at Holly Springs, MS, 11 storms, 1968-73, Borah and Ashraf (1988)
Porosity	0.07 - 0.11	Agricultural fields, unsaturated soil samples from various studies, Jury, et al. (1991)
Water Content		
0.1 bar	0.04 - 0.20	
15 bar	0.14 - 0.45	
Sat. Hyd. Cond.	0.48 - 3.20	

* Derived estimate for saturated hydraulic conductivity. Note relatively high coefficient of variation under controlled experimental conditions.

** Observed runoff not a parameter or input value, but range of values shown for comparison purposes.

*** Often used as input values to unit hydrograph models and other peak discharge estimation models.

3.2 A MODEL UNCERTAINTY NUMBER

We propose CVm as defined by Eq. 1 as a simple model uncertainty number which reflects the uncertainty in model inputs and model parameters through their coefficients of variation. Uncertainty in model output is not dealt with explicitly, but is implicitly represented by the variation in inputs and parameter values and the associated variations in output through sensitivity analysis.

4. A Measure of Systematic Error

Systematic error is used herein to express the degree a model and its components incorporate the governing equations for the processes represented. A model based on the governing equations for the processes considered would have a low systematic error (i.e. the model system mimics the natural system to a high degree) whereas a model based on correlation between inputs and outputs and which does not include the governing equations would have a high systematic error.

The governing equations of primary interest in rainfall- runoff modeling are:

1. Equation for conservation of mass (continuity eq.),
2. Equation for conservation of momentum (momentum eq.),
3. Equation for conservation of energy (energy eq.),
4. Equations specifying position (x,y,z),
5. Equations specifying velocity

$$\left(\frac{\partial x}{\partial t}, \frac{\partial y}{\partial t}, \frac{\partial z}{\partial t}\right) \tag{2}$$

6. Equations specifying acceleration

$$\left(\frac{\partial^2 x}{\partial t^2}, \frac{\partial^2 y}{\partial t^2}, \frac{\partial^2 z}{\partial t^2}\right) \tag{3}$$

These equations, or most commonly a one-dimensional subset of them, are specified for each component in a model and combined and manipulated until the mathematical model for the component is derived.

4.1 SYSTEMATIC ERROR NUMBER

If NEc is the number of the six governing equations included in a component then it is possible to define a component systematic error number, NSc as

$$NSc = 10.0[(6.0-NEc)/6.0] \tag{4}$$

where the quantity within the brackets is a number between 0 and 1.0, and the coefficient (10.0 in this case) is a scaling factor included to facilitate graphing.

If NSc is summed over all Nc components, the resulting model systematic error number, NSm, is

$$NSm = \sum_{c=1}^{Nc} (NSc)/Nc \tag{5}$$

where NSm is again a number between 0 and 10.

We propose NSm as a simple number reflecting the level of systematic error, with respect to the basic governing equations, contained in a model. This number indicates nothing about how well the governing equations are represented, parameterized, and solved, rather, it merely indicates whether or not the governing equations were included in the model structure. As such, NSm is a measure of the amount of processes-based formulations included in a model and thus is an overall measure of its physical basis.

5. Objective Evaluation of Models

As stated earlier, there is a great need for objective, repeatable methods of selecting the appropriate model for a specific application. Although several subjective techniques undoubtedly exist and are used routinely, advances in hydrologic modeling and the associated increases in model complexity require more objective techniques.

5.1 A SIMPLE METHODOLOGY

We propose that the model complexity number, Nc, the overall noninteractive coefficient of variation, CVm, and the model systematic error number, NSm, be used to quantify model complexity, uncertainty, and systematic error.

5.2 EXAMPLE ANALYSES

One of the earliest and apparently simplest infiltration models is the Phi Index which is an average rate of infiltration, applied to a time-intensity graph (hyetograph) of rainfall, such that the volume of rainfall excess equals the volume of storm runoff. For this and subsequent analyses, we will assume a reference hyetograph made up of 10 time-rainfall intensity pairs or 20 paired numbers. In actual practice, the number of time-rainfall intensity pairs will vary with storm characteristics, measurement equipment, and data processing procedures.

The Phi Index can be quantified as follows. It has one parameter, Phi, and it has 20 input values so n = 21. If we assume m = 4 simulations to determine model sensitivity, then the model complexity number is Nc = nm + 1 = (21)(4) + 1 = 85. From Table 1 if we assume Phi contains all the variation of the saturated hydraulic conductivity plus that due to porosity and initial water content, its coefficient of variation should be selected from near the high range of 0.48 - 3.20. Assume the CV for Phi is 2.0. Further, if we assume the intensity values have a CV comparable to total storm depth (0.44 in Table 1) and if we assume a default value of 0.10 for the time values, then the model uncertainty number, CVm, can be computed as follows CVm = CVp + SUM CVi = 2.0 + 10(0.44) +10(.10) = 7.4. Finally, the systematic error number, NSm is 10.0(6-1)/6 = 8.33 because the Phi Index only satisfies continuity of mass. Therefore, for the Phi Index the model quantification numbers are Nc = 85, CVm = 7.4, and NSm = 8.33.

A comparable analysis for the Runoff Curve Number Model yields one parameter (CN or S) and one input value, P the total storm rainfall. Thus, Nc = (2)(4) + 1 = 9 if we again assume m = 4. If we assume the CN has a CV of about 0.10 and P again has a CV of 0.44 (Table 1), then the uncertainty number is CVm = 0.10 + 0.44 = 0.54. Finally, the Runoff Curve Number Model only satisfies continuity of mass so the systematic error number is NSm = 8.33.

Analysis of the Green-Ampt infiltration equation shows 4 parameters (saturated hydraulic conductivity, Ks; soil porosity, n; the matric potential across the wetting front, Psi; and initial water content, SEi) and the same 20 time-intensity values used previously. With these values, the model complexity number is Nc = (24)(4) + 1 = 97. The model uncertainty number is CVm = CV(Ks) + CV(n) + CV(Psi) + CV(SEi) + 10(.44) + 10(.10). Assume mid-range values for the CV of Ks, n, Psi, and SEi as 1.5, 0.10, .50, and 0.20 so that CVm = 7.7. Finally, the Green-Ampt model satisfies continuity of mass and calculates the position and velocity of the wetting front so its systematic error number is NSm = 10.0(6-3)/6 = 5.0.

The Rational Formula is

$$Q = CIA \tag{6}$$

where Q is peak discharge in cfs, C is a runoff coefficient, I is rainfall intensity in in/h for a time period equal to the time of concentration, and A is the watershed area. The time of concentration, tc, is usually computed from basin characteristics. For example, the Kirpich (1940) formula is of the form

$$tc = K(L^{0.77}/S^{0.385}) \tag{7}$$

where K is a coefficient, L is basin length and S is an approximate average slope for the watershed. One could assume a given value of tc and only use Eq. 6 in the analysis, however, we decided to include time of concentration because of its central role in hydrograph development.

With these equations, the Rational Formula has a model complexity number of Nc = (6)(4) + 1 = 25 because there are 5 parameter values (C,A,K,L,and S) and one input (I). Assuming a CV of about 0.5 for C, 0.44 for I, 0.05 for A, L, and S, and 0.5 for K, the uncertainty number is calculated as CVm = 0.5 + 0.44 + 3(0.05) + 0.5 = 1.59. Because the Rational Formula only satisfies continuity of mass, its systematic error number is NSm = 8.33.

A coupled Green-Ampt infiltration model and kinematic wave model for a plane was described by Stone *et al.* (1992). This model contains all the Green-Ampt parameters and input values plus the following: (1) Slope of the plane, S, (2) Length of the plane, L, (3) Hydraulic roughness coefficient, C, (4) Percent canopy cover, CC, (5) Percent ground cover, GC, (6) Random roughness statistic, RR, (7) Depth-discharge exponent, m, and (8) A time step for calculations, Dt.

With these values there are 12 parameter values and the same 20 time-intensity pairs so that the model complexity number is Nc = (32)(4) + 1 = 129. The coefficients of variation of L, S, Dt are assumed to be 0.05, for C about 0.50 (Table 1, Manning n values), and about 0.10 for CC, G C, RR, and m. These CV's sum to 1.05 and when added to the CV's from the Green-Ampt component produce CVm = 7.7 + 1.05 = 8.75. Finally, the kinematic wave equations satisfy continuity of mass and take into account velocity and position so the overall systematic error number for the model is NSm = 5.0. Results of the model quantification examples are summarized in Table 2.

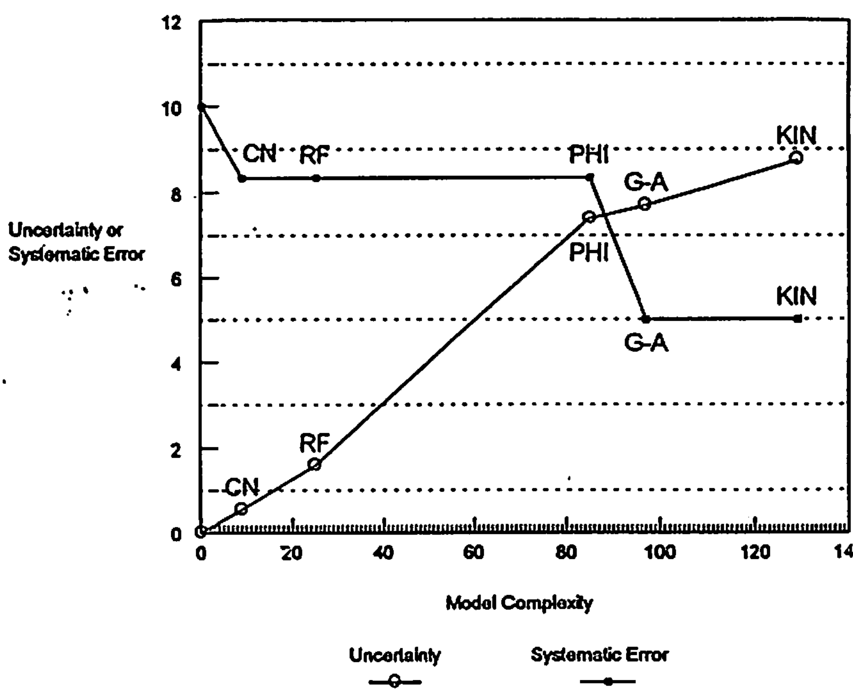
Values from Table 2 are plotted in Fig. 2. Notice that the order of increasing complexity of the 5 models is (1) Runoff Curve Number (CN), (2) Rational Formula (RF), (3) Phi Index (PHI), (4) Green-Ampt Infiltration (G-A), and (5) Kinematic Wave Model (KIN). For these examples, there is an almost linear increase in model uncertainty number with increasing model complexity number. The overall trend is for model systematic error to decrease with increasing model complexity number.

The Runoff Curve Number Model and the Rational Formula have relatively low complexity and uncertainty but high systematic error. In contrast, the apparently simple Phi Index is characterized by high complexity and uncertainty and high systematic error because it requires the full rainfall hyetograph as input. The Green-Ampt Infiltration Model requires little increase in complexity or uncertainty over the Phi Index but exhibits significantly less systematic error (Fig. 2). Based on these criteria only, there would appear to be little or no advantage of simplicity of the Phi Index over the Green-Ampt Infiltration Model but a heavy penalty in systematic error.

TABLE 2. Summary of model quantification examples

Model	Complexity	Uncertainty	Systematic Error
Phi Index	85	7.40	8.33
Runoff Curve Number	9	0.54	8.33
Green-Ampt Infiltration	97	7.70	5.00
Rational Formula	25	1.59	8.33
Kinematic Wave	129	8.75	5.00

Figure 2. Illustration of relationships between model complexity, uncertainty, and systematic error for the 5 examples.



6. Future Considerations

We have discussed model classification and developed and illustrated examples of model quantification in terms of complexity, uncertainty, and systematic error. We now briefly discuss selected future potential applications of model quantification techniques.

6.1 MODEL SELECTION IN DECISION SUPPORT SYSTEMS

Increasingly, land and natural resource systems management will require the application of multiobjective decision making. Questions and decisions will involve basic resources: soil, water, air, plants, and animals; human resources: economics, recreation, esthetics, cultural heritage, and preservation; and broad societal concerns such as resource sustainability based on productivity, the environment, economics, equity, and social policy goals. As the data bases, simulation models, objectives, policies and regulations, monitoring, and reporting requirements become more comprehensive and more complex, computer-based decision support systems (DSS) will be required to assist the decision makers.

Because of the complexity of the problems and the lack of complete data bases, the DSS will use imbedded simulation models to provide values of the multiobjective criteria, or decision variables, used in the multiobjective analyses. Because the decision theory associated with multiobjective decision making is itself complex and mathematically-based, it too will be imbedded within future decision support systems (i.e. Yakowitz, *et al.*, 1992).

Techniques similar to the model classification criteria and model quantification methodology summarized herein could provide the DSS with objective ways of selecting the appropriate model once the land management-natural resource problem has been defined. This procedure of problem definition (in the rigorous systems engineering sense) and the subsequent selection of suitable simulation models to address the problem lead to the discussion of appropriate technology.

6.2 A SYSTEMATIC APPROACH TO APPROPRIATE TECHNOLOGY

Appropriate technology has been a goal and has been practiced since the start of civilization (see for example, Albertson, 1991). According to Albertson (1991) recent emphasis on appropriate technology is primarily due to Schumacher (1973) and his concern for shortcomings of policies of the industrialized nations.

Appropriate technology has often been discussed in the context of transfer of technology from the industrial countries to the less developed countries. This interpretation is too restrictive and eliminates the need for appropriate technology within as well as between all levels of organizations, societies, and nations.

Albertson's (1991, p. 229) definition is:

"Appropriate technology is the appropriate use of knowledge, skills, organization and machinery for the production of goods and services which are desired by those people being served. These goods and services are provided in a way that: is compatible with nature and the environment, uses only renewable resources including energy resources, benefits people equally and to the maximum extent possible, and is based on an economic system where the service motive is combined equally with the profit motive."

A central concept in this definition of appropriate technology is the matching of technology used to assist in providing goods and service with the needs and desires of the people being served in a socially, environmentally, economically, and natural resource-base sustainable manner.

Within the narrower context of this paper, a key concept is to match the appropriate simulation model with the users' needs, preferences, and resources as specified in the problem definition. Perhaps model quantification methodology such as described herein can assist in selecting the appropriate simulation models to use in addressing specific problems and thus contribute to the development of a systematic approach for development and application of appropriate technology.

7. References

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